A Study on Off-Line Signature Verification using Directional Density Function and Weighted Fuzzy Classifier

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ABSTRACT

This paper is concerning off-line signature verification using a density function which is obtained by convolving the signature image with twelve-directional 5x5 gradient masks and the weighted fuzzy mean classifier. The twelve-directional density function based on Nevatia-Babu template gradient is related to the overall shape of a signature image and thus, utilized as a feature set. The weighted fuzzy mean classifier with the reference feature vectors extracted from only genuine signature samples is evaluated for the verification of freehand forgeries. The experimental results show that the proposed system can classify a signature whether it is genuine or forged with more than 98% overall accuracy even without any knowledge of varied freehand forgeries.

가중치 퍼지분류기와 방향성 밀도함수를 이용한 오프라인 서명 검증에 관한 연구

한수환† · 이종극††

요 약

본 논문에서는 12개의 방향성 5x5 그라디언트 마스크를 서명영상에 적용하여 추출한 밀도함수와 가중치 평균 퍼지분류기를 사용하여 오프라인 서명검증기법을 연구하였다. Nevatia-Babu 그라디언트 마스크에 근간을 두고 추출한 12 방향에 대한 밀도함수는 서명영상의 전체적인 형태와 연관이 있어 본 연구의 특징벡터로 사용되었다. 가중치 평균 퍼지분류기의 판단기준이 되는 특징벡터들의 집합은 친필 서명샘플들에서만 추출되어 위조서명의 검출에 적용되었다. 본 논문의 실험결과는 제안된 시스템이 다양한 위조서명에 관한 어떤 사전지식이 없다할지라도 98% 이상의 높은 검증률로 서명영상의 진위여부를 가려낼 수 있음을 보였다.

1. Introduction

The verification of handwritten signature is an important research area, which has the numerous applications in banking, crime investigation and other high security environments. Automatic handwritten signature verification systems(AHSVS) are either on-line or off-line, which are differentiated by the data acquisition method[1,2]. In an on-line system, signature traces are acquired in real time with digitizing tablets, instrumented pens, or other specialized hardwares during the signing process. In an off-line system, signature images are acquired with scanners or cameras after the complete signatures have been written. Most of AHSVS are on-line systems which utilize dynamic features to achieve excellent verification results[1][3]. The problem of off-line signature verification can be stated simply as: given a signature and knowing the identity of the person whose signature is presented (i.e., by credit card number), verify that

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the signature belongs to that person or declare it to be a forgery. This task is more difficult than real-time input because the kinematic information of handwriting is lost.

A wide range of techniques have been applied in the past to solve the more difficult off-line signature verification problems such as elastic image matching techniques to reduce random forgery acceptance rate[4,5], extended shadow-coding method used as a global signature shape descriptor [6], and 2-D FFT spectral method[7]. Nagel and Rosenfeld described a system for automatic detection of freehand forgeries based on characterizing handwriting strokes in terms of a set of kinematic parameters[8]. For the case when the actual (or true) signature and the forgery are very similar, Ammar *et al.* introduced an effective approach based on pressure features of the signature image[9]. In recent years, a classical back-propagation neural network classifier with the directional probability of the gradient on the signature image[10] and with geometric features [11,12] were introduced for the detection of random forgeries.

One of the important factor on off-line AHSVS is to select an appropriate classifier. If a back-propagation (BP) neural classifier is trained with only authentic signatures, it always responds that every signature presented is true because of the characteristics of BP[13]. Therefore the network should be trained with both genuine and forged signatures. Under the real world environment, only a few forged signature samples are available. And a backpropagation structure has some typical problems such as learning rate limitations, difficulty in selecting the optimal number of hidden units, which shows that it might be affected by the characteristics of input patterns. In this paper, a triangular fuzzy membership function and a weighted fuzzy mean are utilized as a classifier without any knowledge of forged signatures. This fuzzy classifier has a simple structure and it can easily improve the classification results by a weighted fuzzy mean extracted from analyzing the incoming feature vectors.

Another important factor is to extract feature vectors representing the characteristics of signature images. Off-line AHSVS use either global [4-7,10], statistical[9] or geometic features[8,11,12]. The use of global features which can abstract the overall shape information of the signatures can provide a faster access mechanism for the signature data because local and structural features require computationally expensive technique. In this paper, a global feature based on twelve-directional 5×5 gradient masks is presented. The approach taken for the feature extraction is as follows. The first step involves scanning actual signatures. Signatures that are written in a specified area of 0.5" by 2" are scanned and digitized with 256 dots per inch, and stored in a 128 by 512 pixel matrix, according to its gray level representation (quantified into 256 levels). The second step is to extract the signature image from the background after noise reduction. The third step involves the choice of orientation and its gradient amplitude for each pixel on the entire signature images by using twelve-directional 5×5 Nevatia-Babu gradient masks[14]. After the normalization, this twelve-directional density function which preserves the overall shape information of the signature is used as a feature set. This feature vector is fed into the weighted fuzzy mean classifier to verify a signature whether it belongs to a genuine or forgery. The overall processing steps are shown in figure 1.

The design of a complete AHSVS which is able to cope with all classes of forgeries (random, freehand, and traced [1]) is a very difficult task because of computational resources and algorithmic complexity[15]. A better solution might be to subdivide the decision process in a way to eliminate rapidly gross forgeries like random or freehand forgeries. Thus a two stages AHSVS seems to be a more practical solution to the problem[10]. In this

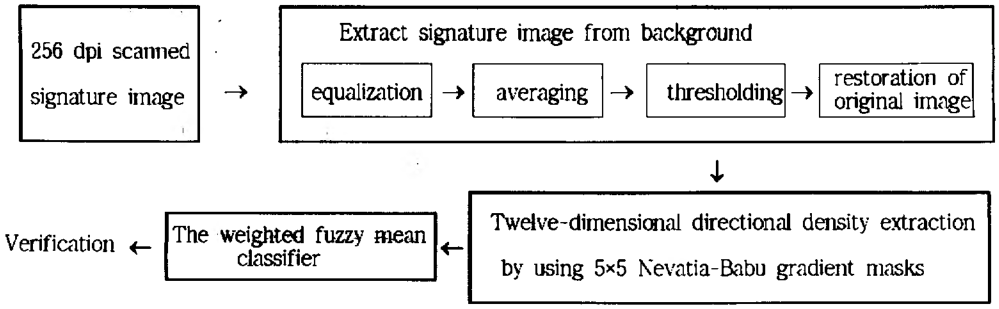

Fig. 1. Overall processing flowchart for freehand forgery detection.

study, only the freehand forgeries which are written in a forger's own handwriting without knowledge of the appearance of the genuine signature are considered, which means this paper focuss on the definition of the first processing stage of a complete AHSVS.

2. Preprocessing stage and Feature extraction

Preprocessing Stage : The goal of preprocessing stage is to extract the signature image from the noisy background. In this portion of the study, the four step preprocessing operations proposed by Ammar *et al.* are used[9]. The first step is to equalize and reduce the background by using equations (1) and (2) as follows.

$$p'(i,j) = p(i,j) - \frac{1}{m}\sum_{l=1}^{m} p(l,j) \quad (1)$$

$$(1 \le i \le m,\ 1 \le j \le n)$$

$$p''(i,j) = p'(i,j) \quad \text{if} \quad p'(i,j) > 0, \quad (2)$$

$$\textit{otherwise} \quad p''(i,j) = 0$$

where $p(i,j)$: the original image, $p'(i,j)$: the equalized image, $p''(i,j)$: the equalized image after clipping, and m by n is the size of the image (128 by 512). Noise reduction is accomplished by the averaging process shown in equation (3) to the entire signature image.

$$\bar{p}(i,j) = \frac{1}{9}\sum_{l=i-1}^{i+1}\sum_{k=j-1}^{j+1} p''(l,k) \quad (3)$$

where $\bar{p}(i,j)$ is the averaged image. After this phase, the signature becomes separable from the background by thresholding. The threshold value, *THD*, is automatically selected based on an entropy method proposed by Kapur *et al* [16]. Next, the original density information is restored in the image by using equation(4).

$$\hat{p}(i,j) = p(i,j) \quad \text{if} \quad \bar{p}(i,j) > THD, \quad (4)$$

$$\textit{otherwise} \quad \hat{p}(i,j) = 0$$

where $\hat{p}(i,j)$: the extracted image and $p(i,j)$: the original image. More details about algorithms and a sample signature before and after the preprocessing stage are found in [9][17].

Feature Extraction: Input to the weighted fuzzy mean classifier for the verification is the twelve-directional density function abstracted from the incoming signature image. It depends on the overall shape of the signature image, and is assumed to have enough information for the detection of freehand forgeries. In the gradient computation process, the gain normalized 5×5 masks developed by Nevatia and Babu[14] are utilized to detect the orientation and amplitude of the edges. They are shown in figure 2.

The twelve-directional gradient masks $M_m(i,j)$ are convolved with each pixel on the entire signature image, which is shown in equation (5).

$$G_m(i,j) = M_m(i,j) \otimes S(i,j), \quad m = 1,2,3,\ldots,12 \quad (5)$$

$$\frac{1}{1000}\begin{bmatrix} 100 & 100 & 0 & -100 & -100 \\ 100 & 100 & 0 & -100 & -100 \\ 100 & 100 & 0 & -100 & -100 \\ 100 & 100 & 0 & -100 & -100 \\ 100 & 100 & 0 & -100 & -100 \end{bmatrix}$$

M_1: (0 *degrees*)

$$\frac{1}{1102}\begin{bmatrix} 100 & -32 & -100 & -100 & -100 \\ 100 & 78 & -92 & -100 & -100 \\ 100 & 100 & 0 & -100 & -100 \\ 100 & 100 & 92 & -78 & -100 \\ 100 & 100 & 100 & 32 & -100 \end{bmatrix}$$

M_2: (30 *degrees*)

$$\frac{1}{1102}\begin{bmatrix} -100 & -100 & -100 & -100 & -100 \\ 32 & -78 & -100 & -100 & -100 \\ 100 & 92 & 0 & -92 & -100 \\ 100 & 100 & 100 & 78 & -32 \\ 100 & 100 & 100 & 100 & 100 \end{bmatrix}$$

M_3: (60 *degrees*)

$$\frac{1}{1000}\begin{bmatrix} -100 & -100 & -100 & -100 & -100 \\ -100 & -100 & -100 & -100 & -100 \\ 0 & 0 & 0 & 0 & 0 \\ 100 & 100 & 100 & 100 & 100 \\ 100 & 100 & 100 & 100 & 100 \end{bmatrix}$$

M_4: (90 *degrees*)

$$\frac{1}{1102}\begin{bmatrix} -100 & -100 & -100 & -100 & -100 \\ -100 & -100 & -100 & -78 & 32 \\ -100 & -92 & 0 & 92 & 100 \\ -32 & 78 & 100 & 100 & 100 \\ 100 & 100 & 100 & 100 & 100 \end{bmatrix}$$

M_5: (120 *degrees*)

$$\frac{1}{1102}\begin{bmatrix} -100 & -100 & -100 & -32 & 100 \\ -100 & -100 & -92 & 78 & 100 \\ -100 & -100 & 0 & 100 & 100 \\ -100 & -78 & 92 & 100 & 100 \\ -100 & 32 & 100 & 100 & 100 \end{bmatrix}$$

M_6: (150 *degrees*)

$$\frac{1}{1000}\begin{bmatrix} -100 & -100 & 0 & 100 & 100 \\ -100 & -100 & 0 & 100 & 100 \\ -100 & -100 & 0 & 100 & 100 \\ -100 & -100 & 0 & 100 & 100 \\ -100 & -100 & 0 & 100 & 100 \end{bmatrix}$$

M_7: (180 *degrees*)

$$\frac{1}{1102}\begin{bmatrix} -100 & 32 & 100 & 100 & 100 \\ -100 & -78 & 92 & 100 & 100 \\ -100 & -100 & 0 & 100 & 100 \\ -100 & -100 & -92 & 78 & 100 \\ -100 & -100 & -100 & -32 & 100 \end{bmatrix}$$

M_8: (210 *degrees*)

$$\frac{1}{1102}\begin{bmatrix} 100 & 100 & 100 & 100 & 100 \\ -32 & 78 & 100 & 100 & 100 \\ -100 & -92 & 0 & 92 & 100 \\ -100 & -100 & -100 & -78 & 32 \\ -100 & -100 & -100 & -100 & -100 \end{bmatrix}$$

M_9: (240 *degrees*)

$$\frac{1}{1000}\begin{bmatrix} 100 & 100 & 100 & 100 & 100 \\ 100 & 100 & 100 & 100 & 100 \\ 0 & 0 & 0 & 0 & 0 \\ -100 & -100 & -100 & -100 & -100 \\ -100 & -100 & -100 & -100 & -100 \end{bmatrix}$$

M_{10}: (270 *degrees*)

$$\frac{1}{1102}\begin{bmatrix} 100 & 100 & 100 & 100 & 100 \\ 100 & 100 & 100 & 78 & -32 \\ 100 & 92 & 0 & -92 & -100 \\ 32 & -78 & -100 & -100 & -100 \\ -100 & -100 & -100 & -100 & -100 \end{bmatrix}$$

M_{11}: (300 *degrees*)

$$\frac{1}{1102}\begin{bmatrix} 100 & 100 & 100 & 32 & -100 \\ 100 & 100 & 92 & -78 & -100 \\ 100 & 100 & 0 & -100 & -100 \\ 100 & 78 & -92 & -100 & -100 \\ 100 & -32 & -100 & -100 & -100 \end{bmatrix}$$

M_{12}: (330 *degrees*)

Fig. 2. Twelve-directional Nevatia-Babu template gradient masks.

where $M_m(i,j)$: the m^{th} directional gradient mask, $S(i,j)$: a pixel on the signature image, and $G_m(i,j)$: the m^{th} directional gradient amplitude. The amplitude and orientation for each pixel are determined by the direction of the largest gradient, which is shown in equation (6) and (7).

$$G(i,j) = \max[|G_1(i,j)|, |G_2(i,j)|, \cdots |G_{12}(i,j)|] \quad (6)$$

$$A(i,j) = m \text{ (the directional index of the largest gradient)} \quad (7)$$

where $G(i,j)$ and $A(i,j)$: gradient amplitude and orientation on signature pixel (i,j). In this paper, the directional intensity of the entire signature pixels is investigated for feature extraction. Thus the twelve-dimensional feature vector is abstracted by equation (8).

$$F(A(i,j)) = \sum_{i=1}^{128} \sum_{j=1}^{512} G^2(i,j) \quad (8)$$

According to equation (8), the feature value, $F(A(i,j)=m)$, is weighted more significantly for the pixels located on the well defined edge of the signature line by square of $G(i,j)$ to preserve the overall shape information. After this stage, $F(m)$ should be normalized for size. Finally, the directional density function of the signature image, $NF(m)$, is found by equation (9).

$$NF(m) = \frac{F(m)}{\sum_{m=1}^{12} F(m)} \quad where \quad m = 1, 2, \ldots, 12 \quad (9)$$

The directional density function of each incoming signature, $NF(m)$, is utilized as a feature vector to be an input of the fuzzy mean classifier for verification. It has an invariance property with respect to size (scale) and shift (translation), but it is sensitive to rotations. Figure 3 shows some samples of genuine and forged signatures and their feature vectors, $NF(m)$. The directional density values of two genuine signatures, (a) and (b) shown in figure 3, are very similar together, but different from feature values of freehand forger (c) and (d).

3. Weighted Fuzzy Mean Classifier

In general, a fuzzy classifier depends on the type of fuzzy membership function and the calculation method of mean value for membership grades[18]. The most popular types for fuzzy membership function are triangle and trapezoid shown in figure 4

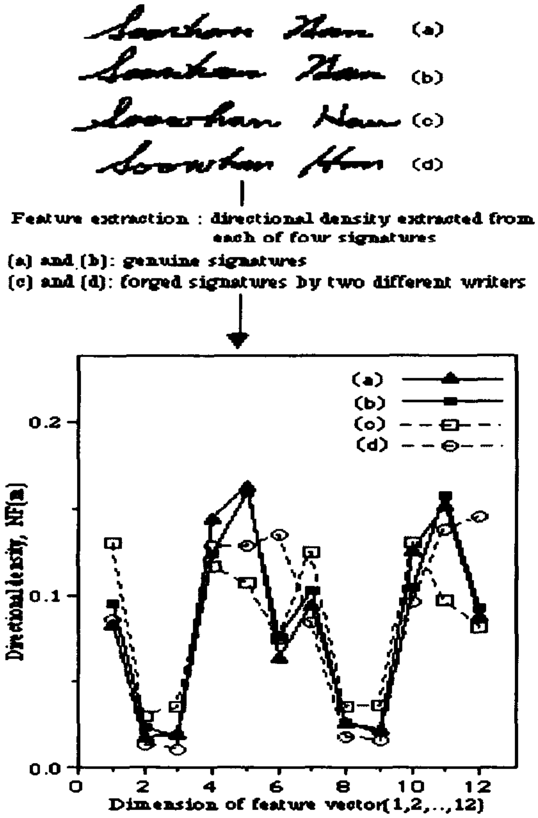

Fig. 3. samples of genuine and forged signatures and their twelve-directional density function, NF(m).

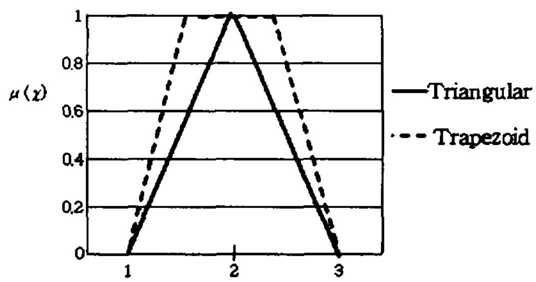

Fig. 4. Triangular and trapezoid fuzzy membership function.

[19]. And the arithmetic mean written in equation (10), the harmonic mean in equation (11) and the weighted mean in equation (12) are widely used for the calculation of mean value[20].

$$h_1(\mu_1(x_1), \mu_2(x_2), \cdots, \mu_n(x_n)) = \frac{1}{n} \sum_{i=1}^{n} \mu_i(x_i) \quad (10)$$

$$h_{-1}(\mu_1(x_1), \mu_2(x_2), \cdots, \mu_n(x_n)) = \frac{n}{\sum_{i=1}^{n} \frac{1}{\mu_i(x_i)}} \quad (11)$$

$$h_w(\mu_1(x_1), \mu_2(x_2), \cdots, \mu_n(x_n); w_1, w_2, \cdots, w_n) = \sum_{i=1}^{n} \mu_i(x_i) \cdot w_i, \quad (\sum_{i=1}^{n} w_i = 1) \quad (12)$$

where μ_i and w_i are a membership grade and a weight for an i^{th} feature value, x_i , respectively, and n is the dimension of incoming feature vector (12 in this paper).

The proposed fuzzy classifier in this study uses the triangular fuzzy membership function and the weighted fuzzy mean method with each variance of the twelve-dimensional reference feature set utilized as the weights, w_i. The triangular type of fuzzy membership function is easy to apply where the only one reference feature set, which is the arithmetic mean of feature values of reference signature samples, is used as in this paper.

This type of fuzzy classifier does not require a training stage while the neual network structure does. In the experimental process, the membership functions for each of twelve-dimensional feature values are simply constructed by using the reference feature set and utilized for the verification of an incoming signature without any training procedure. The evaluation process is much simpler and easier than that of the conventional neural network classifier. Another advantage of this fuzzy classifier is the use of a variance as a weight. In general, it is hard for the neural classifiers to improve the performance results because they significantly depend on the architectures, learning algorithm and training order[13,21]. However, the improvement of recognition results for this fuzzy classifier is easily achieved by using the variances as the weights, which are extracted from each of the twelve-dimensional directional density values in reference feature set.

The construction of triangular membership functions and weights, and the verification process with and without weights are shown and discussed

in the experimental section.

4. Experimental procedure and Verification results

The signature samples used in the experimental procedure consist of two data sets. Each of them contains 80 signatures taken from four different writers. One of four different writers was chosen as a target and asked to write his own name twenty times on a white sheet of paper using similar black ink ball point pens, with no constraint on the handwriting process, except for the 0.5" by 2" box where the signatures have to be written. Three of the remaining writers were assigned to be forgers. Each of the forgers was asked to write the targeted name twenty times in his/her own handwriting. The forgers were not allowed to study the samples of the original signature. Thus 20 genuine signatures and 60 freehand forgeries were collected for each data set. The target for the data set 1 is "Soowhan Han", and the other is "Dohong Jeon". Some samples of genuine and forged signatures for data set 1 and 2 are shown in fig. 5 and 6, and their twelve-directional density features in fig. 7 and 8, respectively.

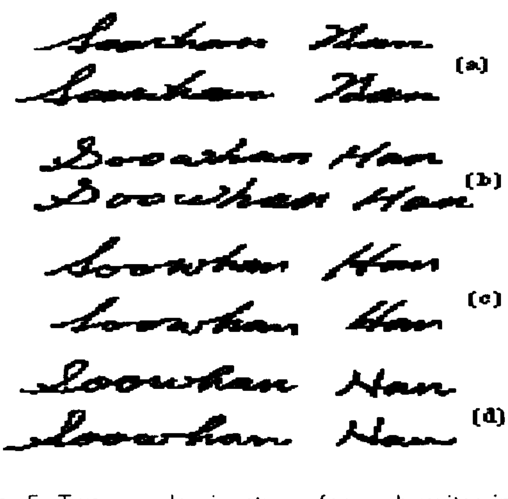

Fig. 5. Two sample signatures for each writer in data set 1. ((a): genuine, (b)-(d): freehand forgeries from three other writers)

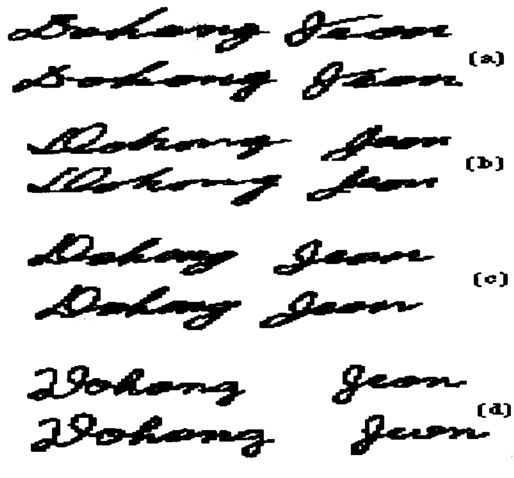

Fig. 6. Two sample signatures for each writer in data set 2. ((a): genuine, (b)-(d): freehand forgeries from three other writers)

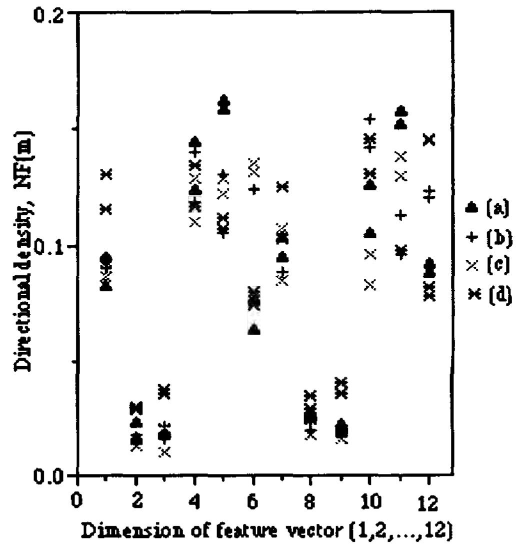

Fig. 7. Twelve-dimensional feature values extracted from signature samples shown in figure 5.

In the experimental procedure, two different scenarios of classification were carried out. The first one treated the four groups of signatures by four writers as four classes, and the fuzzy classifier assigned it to one of the classes when an unknown signature was presented. It is called the writer identification process. The other scenario is the signature verification process. In this scenario, a

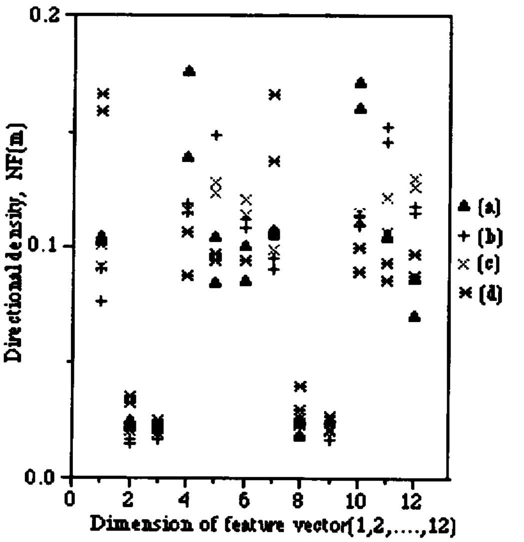

Fig. 8. Twelve-dimensional feature values extracted from signature samples shown in figure 6.

labeled signature was presented to the fuzzy classifier, and it decided whether the signature was that of the person indicated by the label or was forgery. The construction of a fuzzy classifier and the classification process under two different scenarios were done by as follows.

Writer Identification : In this scenario, the twelve fuzzy membership functions for each writer are established by using each of the twelve-dimensional directional density values of the reference feature set. The fuzzy membership functions are defined by equation (13), (14) and (15).

$$\mu_i(x_i) = \frac{2.5(x_i - f_i)}{f_i} + 1 \quad \text{if} \quad x_i < f_i \tag{13}$$

$$\mu_i(x_i) = -\frac{2.5(x_i - f_i)}{f_i} + 1 \quad \text{if} \quad x_i \geq f_i \tag{14}$$

$$\mu_i(x_i) = \begin{matrix} \mu_i(x_i) & \text{if} & \mu_i(x_i) \geq 0 \\ 0 & \text{if} & \mu_i(x_i) < 0 \end{matrix} \tag{15}$$

where x_i is an i^{th} feature value of input signature image, f_i is an i^{th} feature value of reference feature set, and $\mu_i(x_i)$ is a membership grade for x_i.

All of membership functions are configured as a triangular type shown in figure 9, and the membership grade for a feature value over or below 40% of reference feature value becomes zero according to equations (13)-(15). The total number of fuzzy membership functions in this senario becomes 48 (12×4 : the one membership function for each of twelve-dimensional reference feature values x four different writers).

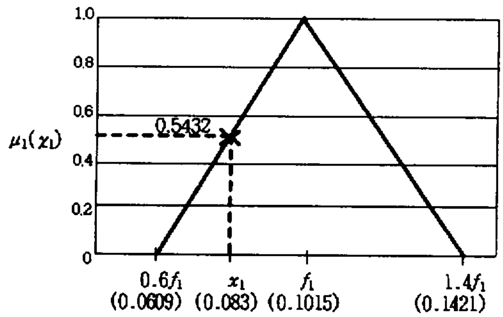

Fig. 9. A fuzzy membership grade for the first feature value extracted from signature sample shown in figure 5-(a).

Next, the variances of each of the twelve-dimensional feature values in the reference feature set for four different writers are derived after normalization. They are shown in equation (16) for normalization and equation (17) for variances. Those variances are utilized as the weights for identification process.

$$nf_{ij} = \frac{f_{ij}}{\sum_{j=1}^{4} f_{ij}} \tag{16}$$

where f_{ij} is the i^{th} feature value of writer **j** in reference feature set and nf_{ij} is a normalized i^{th} feature value of writer **j**.

$$vr_i = E[(nf_{ij} - m_i)^2] \tag{17}$$

where m_i is a mean of normalized i^{th} feature values in reference feature set for four different writers and vr_i is their variance.

In the identification process, the twelve-di-

mensional directional density values of the incoming signature image are applied to the corresponding fuzzy membership functions of the reference feature set for each of four different writers and the membership grades are computed by equations (13)-(15). These twelve membership grades with each of four reference feature set present the degree of similarity with each of four different writers. Finally the variances shown in equation (17) are utilized as the weights by equation (18), and the weighted fuzzy mean values of the membership grades are computed by equation (19). Any of four reference sets with the largest weighted fuzzy mean value is selected as an identification result for the incoming signature image. By using the weight shown in equation (19), a membership grade of the i^{th} feature value which is significantly different between four writers is more emphasized in the identification process.

$$w_i = vr_i \quad (i=1,2,\ldots,12) \tag{18}$$

where w_i is a weight for the i^{th} feature value.

$$h_j(\mu_{1j}(x_1), \mu_{2j}(x_2), \ldots\ldots, \mu_{12j}(x_{12}); w_1, w_2, \ldots\ldots, w_{12}) = \sum_{i=1}^{12} \mu_{ij}(x_i) \cdot w_i \tag{19}$$

where h_j is a weighted fuzzy mean value for a writer j, and μ_{ij} is an membership grade for the i^{th} feature value of a writer j (j=1,2,3,4 for four different writers).

Two data sets as mentioned before were evaluated in the experimental procedure. Each of two data sets contains 80 signatures taken from four different writers (20 signatures/a person). Five-times independent simulations were performed with a different choice of signature samples for reference feature set, and the results were averaged and summarized in table 1. It is obvious that the fuzzy classifier with the reference set constructed by more signature samples shows the better identification results. And the averaged identification ratios show that the weighted fuzzy mean classifier with twelve-dimensional directional density feature values relatively well identifies the writers even though the only small size of letters is available as signatures on the credit card.

Table 1. Averaged identification results(%) for each of two data set.

data set \ reference feature set	1	2	3	4
data set 1(Soowhan Han)	82.75	88.75	90.25	91.75
data set 2(Dohong jeon)	82.00	86.50	87.50	88.00

* reference feature set 1 is the feature values extracted from randomly selected only one signature image for each of four writers.
* reference feature set 2,3 and 4 are the averaged feature values extracted from randomly selected three, five and ten signature images for each of four writers, respectively.

Signature Verification: In neural network approach to signature verification problems, the variety of forged signatures is usually needed to train the neural classifier for the high performance [13,17]. However, under the real world environment, only a few forged signature samples are available. In this study, a fuzzy mean classifier without any knowledge of forged signatures is presented to decide an incoming signature whether it belongs to a genuine or forged signature.

Under this verification scenario, the reference feature set is constructed only for the genuine signatures and the weights for each of twelve-dimensional feature values are derived by equation (20).

$$w_i = 1 - \frac{vr_i - \min(vr_i)}{\max(vr_i) - \min(vr_i)} \tag{20}$$

where w_i is a weight for the i^{th} feature value; vr_i is a variance of i^{th} feature values in reference feature set only for genuine signature samples; $\min(vr_i)$ and $\max(vr_i)$ are an minimum and an maximum in vr_i : i=1,2,..,12, respectively. By the equation (20), the i^{th} dimension of feature values which has the minimum variance among twelve-dimension of reference feature set has a larger

weight, and it means the i^{th} feature values which are not significantly changed between genuine signature samples are more weighted. It has a benefit on verification process because the reference feature set is constructed with only genuine signature samples. The verification results with weights and without weights are compared in table 2 and 3.

In the verification process, the membership grades of the feature values for an incoming signature image are derived by equations (13)-(15) as mentioned before. Next, the fuzzy mean value with the weights is extracted by equation (21) and the signature is verified by equation (22). In case of without weights, h shown in equation (21) is simply a sum of membership grades of the twelve-dimensional feature values

$$h(\mu_1(x_1), \mu_2(x_2), \ldots\ldots, \mu_{12}(x_{12}); w_1, w_2, \ldots\ldots, w_{12}) = \sum_{i=1}^{12} \mu_i(x_i) \cdot w_i \quad (21)$$

where h is a weighted fuzzy mean value for an incoming signature image, μ_i is a membership grade of the i^{th} feature value, and w_i is a weight shown in equation (20).

$$\begin{aligned} &h \geq THD \text{ accepted a genuine signature} \\ &h < THD \text{ rejected a forged signature} \end{aligned} \quad (22)$$

where THD is a threshold value. In the experiments, two different thresholds are selected. One is 85% of the weighted fuzzy mean value for randomly selected one of reference signature samples (a high THD), and the other is 65% of it (a low THD). Each of two data sets which has 20 genuine signatures and 60 freehand forgeries was evaluated with both of two different thresholds, and also tested with weights and without weights. Five independent simulations were performed with a different choice of signature samples for reference feature set, and the verification results were calculated by using the expressions shown in eqs. (23)-(25) and averaged. They are summarized in table 2 for data set1 and table 3 for data set 2.

Ratio of Correct Acceptance(RCA) =

$$\frac{\textit{num. of correctly accepted genuine signatures}}{\textit{total num. of tested genuine signatures}} \times 100 \quad (23)$$

Ratio of Correct Rejection (RCR) =

$$\frac{\textit{num. of correctly rejected forgeries}}{\textit{total num. of tested forgeries}} \times 100 \quad (24)$$

System Reliability (SR) =

$$\frac{\textit{num. of correctly accepted genuine signatures} + \textit{num. of correctly rejected forgeries}}{\textit{total num. of tested signatures}} \times 100 \quad (25)$$

The reference feature set 1 is constructed with only one genuine signature sample. Thus the weights derived by the variance of each dimensional feature value of reference signature samples cannot be applied to the verification process. The RCA with reference feature set 1 is relatively low when a high THD was used, which means the fuzzy classifier with a high THD made a lot of false rejections. However a THD does not significantly affect the verification results where more signature samples are available for the reference feature set. It is shown in SR with reference feature set 3 & 4. And the fuzzy classifier with the reference feature set constructed with more signature samples shows the better verification ratios. From table 2 & 3, it is clear that the verification results can be easily improved by using the weights, and the system reliability with reference feature set 4, SR, is reached over 99% for both of two data sets. These results mean that the weighted fuzzy mean classifier with the twelve-dimensional directional density feature values of the signature images performs relatively well to detect the freehand forgeries.

5. Conclusions

From the high verification results in the experimental process, it is known that the weighted fuzzy mean classifier with the twelve-directional

Table 2. Averaged verification results for data set 1 (Soowhan Han)

verification results(%) \ reference feature set		1	2	3	4
RCA	without weight	90.00 (64.00)	96.00 (96.00)	96.00 (96.00)	99.00 (96.00)
	with weights	-	95.00 (97.00)	100.00 (98.00)	99.00 (100.00)
RCR	without weights	95.33 (99.67)	95.67 (96.33)	96.00 (97.33)	94.00 (96.67)
	with weights	-	99.00 (99.33)	98.33 (99.33)	99.67 (100.00)
SR	without weights	94.00 (90.75)	95.75 (96.25)	96.00 (97.00)	95.25 (96.50)
	with weights	—	98.00 (98.75)	98.75 (99.00)	99.50 (100.00)

* reference feature set 1 is the feature values extracted from randomly selected one genuine signature image.
* reference feature set 2,3 and 4 are the averaged feature values extracted from randomly selected three, five and ten genuine signature images, respectively.
( ) : verification results with a high THD

Table 3. Averaged verification results for data set 2 (Dohong Jeon)

verification results(%) \ reference feature set		1	2	3	4
RCA	without weight	80.00 (68.00)	99.00 (98.00)	100.00 (100.00)	100.00 (100.00)
	with weights	-	99.00 (99.00)	100.00 (100.00)	100.00 (100.00)
RCR	without weights	99.00 (100.00)	96.00 (98.00)	96.00 (98.00)	93.67 (97.33)
	with weights	-	97.67 (99.33)	97.33 (100.00)	99.00 (100.00)
SR	without weights	94.25 (92.00)	96.75 (98.00)	97.00 (98.50)	96.25 (98.00)
	with weights	-	98.00 (99.50)	98.00 (100.00)	99.25 (100.00)

* reference feature set 1 is the feature values extracted from randomly selected one genuine signature image.
* reference feature set 2,3 and 4 are the averaged feature values extracted from randomly selected three, five and ten genuine signature images, respectively.
( ) : verification results with a high THD

density features obtained by convolving the signature image with 5×5 Nevatia-Babu gradient masks performs well to verify an incoming signature whether it is a genuine or forged signature. In the verification process, only the genuine signature samples are utilized for the reference feature set because a few forged signature samples are available under the real world environment. In addition, the verification results are easily improved by using the weights extracted from analyzing the feature values, and in this fuzzy classifier, the training period is not required because the reference feature set can be simply constructed with some of genuine signature samples.

The further research area in a near future should involve an investigation of feature extractions from a signature image which contain more detailed shape information characterizing the genuine signature while still maintaining relatively small dimensionality for inputs to the fuzzy classifier. And for the real world applications, a larger data set with more varied writers should be evaluated.

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